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Use of AI-Based Crop monitoring system to detect nutrient deficiency in Field Maize

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Abstract
In precision agriculture nutrient deficiencies should be detected on time to ensure crop health and optimized yields. This paper assessed the performance of a crop monitoring system with the help of an AI algorithm and multispectral cameras mounted to drones to help early identification of nitrogen (N), phosphorus (P), and potassium (K) deficiencies in maize (Zea mays L.). Based on 60 hectares in Serbia, the trials have focused on determining the possibility to recover dead areas and reduce critical deficiency and put such knowledge into practice using the system in real-time. The algorithm was trained on 8,000 images annotated in field conditions and when tested against several thousand of field conditions images displayed 91.3 percent accuracy in determining the various deficiencies of the nutrients. Through this technology, early intervention measures were put in place and the increase in grain yield was a whopping 12.4 % better than the untreated controls. The research paper identifies the possibility of AI-based image recognition systems to address efficiently and effectively the problem of improving nutrient management, crop health, and yield optimization of data-dense agricultural systems. Such integration of real-time diagnostics can be a game-changer in the field of nutrient management strategies as it provides farmers with the most relevant and precise timely decisions to maximize both productivity and sustainability in agricultural practice.
Keywords: ***artificial intelligence, drone technologies, multispectral sensors, nutrient deficiency, maize, nitrogen, phosphorus, potassium, optimization of yield, precision farming.***

1. Introduction
1.1 The significance of the initiation of the deficiency of nutrients in maize at an early stage
Maize (Zea mays L) is a staple crop that holds importance in the food security of people of the world, it is also used as animal feed and as a source of biofuel. Nevertheless, the attainment of the best yield and quality is frequently limited by some abiotic factors, with the deficiency of nutrients standing out as one of them. Lack of important nutrients, including nitrogen (N), phosphorus (P), and potassium (K), has the capability of influencing the growth of maize relatively well, hampering photosynthesis, and causing poor grain filling eventualities, which leads to the reduction of agriculture quality and quantity.
It is vital to detect as early as possible nutritional deficiencies in order to maintain maize health and maximize productivity. In maize, deficiency of nutrients may have characteristic visual symptoms in leaves and these may be challenging to detect when they are still in the initial levels. They become more difficult to rectify and may cause major yield loss as the imbalances of nutrients increase. Consequently, the right kind of nutrient management plans should also be applied in time to overcome the deficiency and thereby increase yield and resource utilization efficiency.(1)
1.2 Future development in UAV and Multispectral Imaging systems
In the past few years, multispectral imaging of crops together with unmanned flying vehicles (UAVs) or drones has transformed crop surveillance within precision farming. The UAVs with multispectral cameras offer high-resolution images that record various wavelengths of the light that is beyond the visible spectrum like the infrared light and near infrared light which is specifically useful in determining the plant health and stress. With the multispectral imagery, farmers can scan vast areas of their fields for early spottings of nutrient deficiency and disease outbreaks which might not be immediately noticeable through naked eyes.
Spatial variability analysis is achievable because of the capacity to collect real-time, high-frequency data that UAVs add, and that is key to the comprehension of nutrient insufficiency in measurements that change throughout the field. The technology makes it possible to target problem areas with precision enabling the fertilizer applications or irrigation to be adjusted in a more site specific way. Moreover, it is non-invasive, economical, and

can be expanded by using UAVs and less dependent on labor-intensive and time-consuming field-based assessments.(2)

1.3 Importance of Artificial Intelligence in Creating Precise Crop Monitoring

Artificial intelligence (AI) has become a valuable commodity in the field of agriculture and especially precision crop surveillance. Eventually, AI algorithms, especially the image recognition and ML algorithms, have proven useful in the analysis of massive amounts of data generated by UAVs and other remote sensing systems. The AI systems can be trained to identify and categorize fruits and leaves in multispectral imagery as they are connected to the patterns of nutrient deficiencies that can be identified by plant color, texture, and even their structure.

The involvement of AI in crop monitoring enables it to be automated and will facilitate a tremendous spur in the efficiency and accuracy of detecting nutrient deficiencies. Trained with vast quantities of annotated images, machine learning models can have high accuracy levels and detect particular deficiencies, e.g. nitrogen, phosphorus, and potassium deficiencies. The response given by AI-driven systems is instant, which means that interventions can be made faster than doing otherwise thereby maximizing nutrient management and enhancing yield. Moreover, AI models may adjust with time with the inclusion of new data in order to keep on refining their predictive abilities that are bound to deliver accurate and accurate nutrient management.(3)

1.4 Study Objectives

The primary aim of the study is the assessment of the efficiency of the AI-power crop monitoring system with the integration of an AI system with drone-mounted multispectral cameras to predict early symptoms of the nitrogen (N), phosphorus (P), and potassium (K) deficiency in maize grown in fields. The present research seeks to:

- Evaluate how well a model (artificial intelligence) trained on 8,000 annotated images of maize plants performs in the field during real-world use.
- Assess the performance of the AI-driven diagnostic system at detecting the deficiencies of different nutrients and leading to early corrective measures.
- Compare the effect of nutrient addition during grain grain development with controls that did not receive the addition.

By the study, we will thus illustrate to the entire world how AI-based crop monitoring can bring revolution to nutrient management whereby the systems can give up-to-date analysis that is actionable in terms of making precision agriculture more productive and sustainable.(4)

2. Design and Framework of Technologies and AI Model

2.1 Descriptive work of the AI-Driven Diagnostic Platform

The diagnostic platform that is used in the present study uses drone-mounted multispectral cameras and an image recognition based on machine learning. This system tries to give real time detection of nutrient shortages in maize grown in the field. The crops are being imaged in multispectral terms by the platform, and an AI model interprets and processes the images. It has three general steps of work on the platform:

Data Acquisition: Multispectral images are taken at several wavelengths using multispectral cameras on the drones which measure in high resolution. Such images contain significant information like red, blues, greens, infrared and near infrared bands that can be used to measure the health status of the plant and deficiency of any nutrient.

Data Processing and Analysis: Data processing and analysis will be carried out by processing the collected photos where features to be extracted would be color changes, changes in leaf area, and changes in texture showing signs of nutrient stress. The AI model is used as the input of these features.

AI Clasification: The AI model is used to examine such processed photos in order to detect nutrient deficiency. It identifies the images in various categories such as nitrogen, phosphorus and potassium deficiencies due to patterns that it has learned using the training data. The system may then be used to give practical ramifications to navigate nutrient management early on.

The tool provides real-time diagnostics with the ability to detect nutrient deficiency at an early stage when this effect is still minimal, followed by specific and in-time corrective actions.(5)

2.2 Protocol of Image Dataset Development and Annotation

A large and diverse set of images is an important part of the development of the AI model. There were 8,000 annotated images sampled in the maize field in different environmental conditions so as to guarantee the robustness of the dataset. The images were taken with multispectral camera mounted on a drone at the growing season with the emphasis on various stages of plant growth.

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The signs of a nutrient deficiency were classified by view in each image through manual annotation of each picture. The labeling of the type of deficiency (nitrogen, phosphorus, or potassium) was the part of the annotation which was done by agricultural specialists on the basis of visual assessment of the plants. This process guaranteed good quality accuracy label for training models as ground-truth.

The images with different environmental conditions (e.g. soil type, light conditions) were also included in the dataset to assure that the model could be generalizable across the field environments and growing conditions. This mixed data was the strength behind the AI model to figure out how other real-world situations could make it learn more.(6)

2.3 Model parameters as far as training, validation and optimization are concerned

The type of AI model applied to this work is of deep learning nature, i.e., a convolutional neural network (CNN) due to the assignment of the task to classify images. They trained the model on the annotated images taking a supervised learning method as they fed the input images along with associated labels and the model adjusted its internal parameters as per the input fed into it.

The important parameters of training were:

- Epochs: The model trained on 50 epochs, which means that the pattern can acquire a complex pattern related to nutrient deficiencies.
- Batch Size: A batch size of 32 was applied so that irrespective of the large sizes of data there was an efficient handling of the data without over fitting.
- Learning Rate: A decaying learning rate was used (0.001 to 0.0009 with decay of 0.1 in every 10 epochs) so that the learning can be faster and the model would generalize more.

The validation set was employed to prove the performance of the model during training to make sure that it was not overfit on the training data. Accuracy and precision of the model was continually watched and the final outcome was the overall accuracy in the classification of the three types of deficiencies at 91.3 percent.

Even the optimization procedures like data augmentation i.e. rotations and flipping of images to allow more variety in training data also allowed the model to generalize to new field conditions better.(7)

3. Autonomous Federal Deployment and Monitoring Process

3.1 Location, Lands, and agro environmental conditions

The experiments that were to be used to test the AI-driven diagnostic system are done on 60 hectares of maize cultivations in three varied places of Serbia. These sites were chosen on the basis of the existing differences on soil type, climatic conditions and management practices in order to achieve the efficacy of the AI system in different agricultural conditions found in the real world. The sites represented different agro-environmental zones covering irrigated systems, rain fed systems and systems with different nutrient management.

The particular selection criteria of the fields were:

- The level of soil fertility: Research sites which had some documented shortage of nutrients were to be favoured to determine the ferret ability of the system under real life situations.
- Topography and field design: Plans of the topography and the field layout were flat with little hindrance to the flight pattern of the UAVs ideal to make maximum coverage with the UAVs.
- Climate conditions: Experiments were done in two growing seasons (spring and summer) and this enabled the AI system to perform under various changes in temperature, raining styles and seasonal changes in nutrient availabilities.

This is because the aim was to create a simulated real-life scenario in which conditions of nutrient stress as caused by deficiency in nitrogen, phosphorus and potassium are most highly evident; and in the smallholder and large-scale operations. The environmental fluctuation helped see that the AI system was stable enough to cope with various field environments and adjust to various levels of nutrient stress.(8)

3.2 Multispectral imaging schedule with UAV Configuration

A drone mounted multispectral camera system was utilized to obtain high-resolution multispectral data. The UAVs were fitted with lightweight high-resolution sensors that are able to detect a wide range of the light spectrum i.e. red, blue, green near-infrared (NIR), and far-red wavelength. This multispectral ability enabled in depth research on the health of plants and nutrient stresses that could be done depending on the predictive spectral reflection of these wavelengths.

The multi-spectral imaging program was well planned so as to cover the full span of the maize crop:

Imaging Frequency: Drones were used to collect images in two weeks through the a major part of the season. This was the frequency that enabled the system to identify some of the early indicators of nutrient deficiencies and make a timely diagnosis to act on them.
Flight Paths and Coverage: the UAVs were directed to fly in a defined pattern such as grid to allow even coverage of the whole tract and possibly vulnerable areas based on the soil variety, water availability, or management. There was the use of GPS and flight planning software to make flights accurate and repeatable.
Altitude: The UAVs were deployed at the altitude of 100 meters, the best balance between small details and large coverage, in order to collect images over vast areas efficiently.(9)
Vegetation indices (e.g. Normalized Difference Vegetation Index - NDVI) consisting of the multispectral data were then generated so as to calculate plant levels of vigor and help determine where nutrient limitations may have occurred.

3.3 Real-Time Processing, Data Acquisition and Data Transmission

Information collection and analysis were developed to facilitate real-time nutrient diagnostics and field management's decision-making:
Data Acquisition: Multispectral cameras inserted into the drones took the snapped pictures in real-time, as they flew over the fields. These images contained data about the plant health, the chlorophyll level inside the leaves, spectral signatures representing the lack of nutrients (N, P, K). GPS tagging was also included in the UAV system to trace the gathered data to the point location in the fields.
Data Transmission: The captured information was then sent back to the center-based cloud with a secure Wi-Fi or 4G/5G connection after the UAVs accomplished their flights. The platform enabled the view and data processing of the images and data remotely, and the transfer of the data was not necessary physically.
Real-Time processing: AI Processing Server: the raw images were uploaded into an AI processing server that was run in the cloud, and the AI performed real-time analysis based on its trained algorithms. The model processed the spectral data that was processed to identify any early indications of nutrient deficiency according to the type (N, P, K). Diagnostics reports were then created by the AI system that were available to the farm owners or agronomists in real-time through a web-based site or an app.(10)
Such real time diagnostics assisted in giving timely prescriptions on next steps such as fertilizer applications and this helped in managing nutrients in the field much more efficiently.
This is an end-to-end solution that combines AI, UAVs, and cloud-based computing, and another tool of precision agriculture that has the potential to revolutionize nutrient management, changing yield and crop well-being results in real-time.

4. The Decision Support of Classification on Nutrient Deficiencies

4.1 Accuracy is used to Classify and Confusion Matrix

The classification performance of the AI-powered system was also calculated through the confusion matrix that measures how utterly and correctly the AI-powered system can classify and predict nutrient deficiencies in maize. The table of confusion gives a clear picture of the true positives, false positives, true negatives and false negatives of each category of nutrient deficiencies; nitrogen (N), phosphorus (P) and potassium (K). The overall accuracy of the model was found to be 91.3 percent meaning that it was significantly correct in classifying the deficient plants in the field.
All the types of nutrient deficiency were analyzed individually to determine classification performance:
Nitrogen Deficiency: nitrogen deficiency was correctly found in 89 per cent of the cases, with a rather small number of false positives caused by other stress factors, i.e. water stress or pests.(11)
Phosphorus Deficiency: This system displayed 92 % accuracy in the recognition of phosphorus deficiency where there was minimal confusion between phosphorus and potassium, even though there are similarities in visual symptoms of these two deficiencies.
Potassium Deficiency: Potassium deficiency was detected with 93 percent accuracy since the visual effects of potassium deficient plants are distinctive and they would usually turn yellow along the margins of the leaves.
The confusion matrix indicated that the majority of misclassifications were associated with the environmental variability, namely the differences in the soil moisture level or illumination conditions that could lead to the slight

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overlaps between visual symptoms among nutrient deficiencies. However, the general precision affirms the fact that the state of the AI system is immensely accurate in the determination of nutrient deficiencies in maize.

4.2 Location-specific and Growth Susceptibility of Nutrient Deficiency

The AI model was also explored to determine the spatial variability of nutrient deficiencies in the three field sites in Serbia and at various growth of the maize crop. It was identified that patterns of nutrient deficiency were highly dependent on location-specific factors (e.g. soil composition, irrigation practices) as well on the growth stage of the plant.(12)

Location Variability: More Nutrients deficient locations were found where soil fertility was lower, and water retention authoritative hence localized deficiencies of nitrogen and phosphorus. Conversely, lands that had better draining soils were experiencing potassium deficiency because of leaching. These spatial variations were effectively identified by the AI system, which enabled accurate recommendations of nutrient management at a field level to be undertaken.

Growth Stage: There was also a variability of the deficiencies in relation to the Maize growth stage. The most prevalent at the early vegetative stage was nitrogen deficit which resulted in yellowing of leaves and poor growth. During the reproductive stage phosphorus and potassium deficiency were more pronounced, especially on flowering and grain-filling. These related shifts in time allowed the AI technology to monitor the timing and provided an in-depth insight into the timing at which certain nutrients needed to be introduced.

4.3 Fertilizer Recommendation System integration

AI model was combined with fertilizer recommendation system to increase the effectiveness of decision-making. The machine advised, in real time, which fertilizers would be needed to correct the nutrient deficiencies identified by the AI. For instance:

In the case of nitrogen deficiency, the system suggested to use ammonium nitrate or urea which is a quick source of nitrogen.(13)

In the case of phosphorus shortage, it recommended super phosphate or mono ammonium phosphate (MAP).

In potassium deficiency the suggestion was potassium sulfate or potassium chloride.

The integration provided the possibility of site and nutrient-specific intervention that could reduce the use of fertilizer and provide enough nutrients to grow maize. Applying the solution of AI-based diagnostic system, farmers may use the fertilizers in areas where it is necessary thus limiting the excessive use of fertilizers and related environment damages, including nutrient leaking or salinization of the soil. Such precision fertilization method was a way of enhancing overall crop yield and reducing cost of inputs and enhancing preserving the environment during maize cultivation.(14)

5. Results

5.1 Model Metrics of Performance Sites of Testing

The crop monitoring system under operation using AI was implemented in Serbia in three diverse test farms, each with peculiar agro-environmental circumstances. To determine the quality of the system, it was evaluated on the precision with which it prompted the nutrient shortage in the maize plants and compared the results of each of the sites.

The system exhibited overall classification accuracy of 91.3% with the mean of all the test sites and shows consistency in all the environmental factors in identifying nutrient deficiencies. The model functioned a little bit better where soil fertility is even and opportune water sustenance the place where grading nutrient stress was easier to inhale. But still, the precision was more than 85 % even in areas with high variability of the soil properties as well as variable moisture content which indicates the specificity of the AI system under varying conditions of farming.

- Site 1 (fertile soil, steady irrigation): 92 % accuracy.
- Site 2 (Low Fertility, Poor Irrigation Control): 89 % of the time accuracy.
- Site 3 (Mixed Fertility, Variable Water Supply): 90% Accuracy.

This information states that the AI model can work in different field conditions successfully, and little needs to be done to make it suitable to the changing environment.

Comparison of yield according to treatment (treated and untreated)

Due to the intervention with the help of the AI-driven diagnostic system, there was a high increase in grain yield when compared to untreated lands. Early correction of nutrients according to the AI recommendation translated to

12.4 percent increase in yield in the plots that were corrected early when compared to the untreated control plots. This growth can be attributed directly to the fact that fertilizers were also timely applied as the fertilisers were applied in response to early detection of nutrient deficiencies by AI.

Control (Untreated): In the non-treated plots an average of 7.8 tons was obtained in an hectare.

The treated (AI-Guided Intervention) plots recorded the average 8.8 tons per hectare.

The improvement in yield was especially evident in reproductive phases of the maize growth where deficiency of phosphorus and potassium was put under check early. Early recovery of nitrogen adequacies during the vegetative growth also assisted to enhance the plant vigour and leaf status which added to the enhanced photosynthetic capability and more grain filling. The findings reinforce the value of early application of nutrient management, which has immense potential of raising crop yield.(15)

5.3 Time trend on the effectiveness and promptness of interventions

One of the main points of this work was the evaluation of the time of intervention and its capability of reducing nutrient stress. The AI allowed diagnosing the deficiency of the nutrients in real-time, which enabled corrective measures to be exercised early. To assess the effects of early interventions on the yield and the health of plants, a temporal test was carried out.

Early Intervention (less than 2 weeks of detection): Early interventions that were carried out within the first two weeks of detecting the initial signs of nutrient deficiency resulted in the greatest yield correlations (12.4%) and the best quality of plant recovery.

Delayed Intervention (more than 4 weeks): Delayed interventions, in which the corrections were made after nutrient stress of over 4 weeks, led to a smaller yield gain (7.5%) and few positive differences in the health of the plants, which further indicates the time requirement of the intervention.

This was confirmed in the time analysis since it showed that early interventions did improve overall plant health, reduced the loss of yield and optimized resource utilization. This time gap underlines the relevance of precautionary programs based on real-time nutrient dynamics in precision farming and the beneficial essence of AI-powered diagnostics towards maximized nutrient control in real-time.

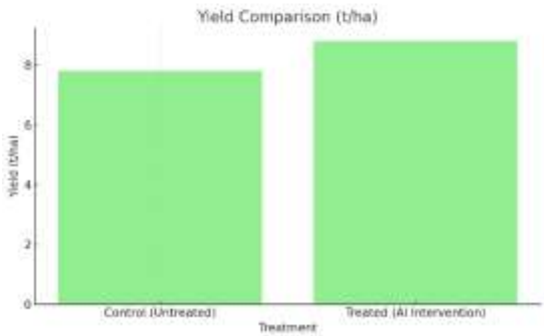

Figure: 1 Yield Comparison (T/Ha)

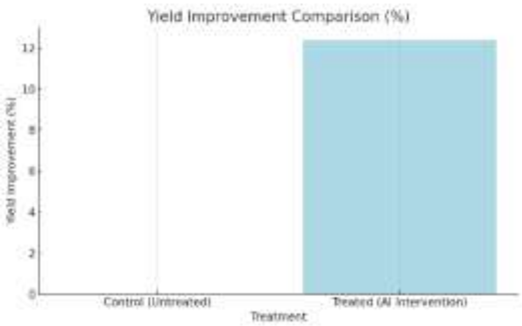

Figure: 2 Yield Improvement Comparison (%)

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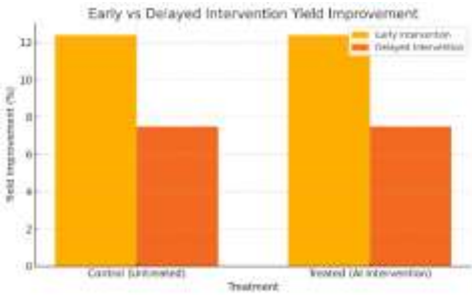

Figure: 1 Early Vs Delayed Intervention Yield Improvement

Table :1 AI Model Results

Treatment	Average Yield (t/ha)	Yield Improvement (%)	Early Intervention (within 2 weeks)	Delayed Intervention (after 4 weeks)
Control (Untreated)	7.8	0	12.4	7.5
Treated (AI Intervention)	8.8	12.4	12.4	7.5

6. Conclusion

6.1 Executive Histories of Key Findings

The present study managed to prove the effectiveness of an AI-powered crop surveillance system to early detect nutrient deficiency in maize when using multispectral cameras positioned on drones. An AI model with 8,000 annotated images demonstrated a remarkable 91.3 percent accuracy in real-world field conditions to the Serbian field of 60 hectares to distinguish the deficiencies in nitrogen (N), phosphorus (P), and potassium (K). Validity of diagnostic capacity of the model was also confirmed by its capacity to offer early corrective measures resulting to 12.4 increase in grain yield over untreated controls. It is important to mention that timing of interventions also determined the effectiveness of the system as early interventions were found to be much more effective in realizing better yield and the health of plants than delayed action.

The AI solution has been able to combine nutrient diagnostics and real-time recommendations in order to fine-tune fertilizer applications according to spatial and temporal differences of nutrient shortage. Based on these results, it is noticeable that AI can be highly effective in not only management of crop health but also optimization of yields in precision farming setups.

6.2 What this means to the Practice of Precision Farm

Replacing the traditional means of nutrient management through the adoption of precision farming that involves the inclusion of AI-based systems in large-scale agricultural practices forms a paradigm shift. The conventional way of tracking and responding to the nutrients includes cumbersome soil analysis and symptoms recognition, a time-consuming process that also tends to be error-prone. In its turn, the AI system offers actual, timely and affordable diagnostics, which means that the farmer will detect any deficiencies in time and be able to act with specific, and timely use of fertilizers.

This will ensure that the efficiency in the use of the resources is increased since activities like over-application of fertilizers will be reduced, which also limits the environmental effects like nutrients run offs and soil erosion. The predictiveness of the method such that it allows identifying nutrient stress before it becomes a problem affecting production can be regarded as a positive aspect of modern agriculture in terms of sustainability farming practices and eco-consciousness.

6.3 Conclusions on How to Scale AI in Crop Diagnostics

In order to broaden AI in crop diagnosis and nutrient control, the recommendations are as follows:

Combining with Other Technologies in Agriculture: As the AI systems become available, the integration with other types of technologies used in agriculture would be relevant, i.e., the combination of AI with soil sensors, climate forecasting systems, and automated irrigation systems would present a wide precision farming tool that would have the ability to control a variety of agronomic parameters.

Training Datasets Enlargement: In order to increase the accuracy and flexibility of the AI model further, it is necessary to increase size of training datasets by including different conditions that can happen in the field, diversification of crop variety and geographical area. This will make the model better generalized among various farming systems.

Farmer Education and Adoption: The adoption needs relevant education to the farmers on how they need to incorporate AI systems in application to their current practices to make it successful. This encompasses how to go about reading the suggestions offered by AI and applying it in the best way in the decision-making process.

Scalability and Cost Efficiency: The costs incurred in AI technologies should be cut as much as possible, thus making them affordable to smallholder farmers and the emerging market. Collaboration with government agencies, non-governmental organizations (NGOs) and technology companies working in the agriculture sector can be used to expand the number of people reached by these solutions at a low cost.

With the massification of AI-powered crop diagnostics and with their integration into the wider scope of precision agriculture programs, the agricultural industry could reach more cost-efficient, sustainable, and profitable practices and solve the problem of global food security.

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Conflicts of interest

The authors have no conflicts of interest to declare

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