Detecting the Growth Rate of Mealybugs Attacking Plants Using DCNN

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Abstract: - Currently, many farmers, due to financial constraints, rely on natural methods to cultivate crops. However, during the crop growth stage, mealybugs a specific type of pest attack these plants, causing significant damage. Since these farmers use organic or natural pest control methods, their ability to completely prevent the spread of these pests is limited. As a result, severe infestations lead to economic losses and even the death of plants. To address this issue, we propose using DCNN (Deep Convolutional Neural Networks) and Anomaly Detection with Regression Analysis to detect the growth rate of mealybugs and provide timely solutions for controlling them. By analyzing the infestation speed and severity, this method can help farmers take preventive measures more effectively. Furthermore, by comparing our proposed approach with previous research studies “Detection of Mealybugs Disease Using Artificial Intelligence Methods”, we demonstrate that our method outperforms earlier solutions in accurately detecting and managing mealybug infestations.

Key-words: - DCNN (Deep Convolutional Neural Networks), Regression Analysis, Mealybug Management, Anomaly Detection, Organic Pest Control.

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1 Introduction

The mealybug is a small insect with a soft body that thrives on various parts of plants, such as leaves, stems, and roots. It feeds by sucking nutrients from the plant, which can lead to the drying of leaves, stunted growth, or, in severe cases, the death of the plant [7] [15]. One of the key characteristics of the mealybug is its white, waxy coating, which serves as a protective layer. These insects are typically found in two distinct color variations: pure white and light reddish shades [8]. They often cluster together on different plant parts and prefer warm and humid conditions, which promote their rapid growth and spread [9]. As they extract nutrients from plants, they weaken them significantly, making the plants more vulnerable to diseases. Some species of mealybugs also act as carriers of viral diseases, contributing to the spread of infections in plants [10]. They are particularly destructive to horticultural and agricultural crops, causing significant damage [11]. To control mealybug infestations, various natural and chemical methods are used. Natural predators, such as insects that feed on mealybugs, help in reducing their population. Additionally, neem oil mixed with water can be sprayed on affected plants to eliminate them. In severe infestations, chemical pesticides are used to control their spread effectively [12].

What Figure 1 aims to clarify is that mealybugs come in different types, with each species having distinct appearances. Some mealybugs are white, while others are pale red in color. These insects feed on plant nutrients by sucking sap from the plants. During reproduction, male and female mealybugs typically mate to produce offspring. However, in some cases, female mealybugs can reproduce without the presence of male mealybugs. The mealybug belongs to the Pseudococcidae family and is generally classified into five categories: kingdom, phylum, class, order, and family [2] [3]. It is a sap-sucking insect, with female mealybugs causing the most damage as they lay a large number of eggs and reproduce rapidly. The primary crops affected by mealybugs include coriander, radish, tomato, potato, grapes, mango, pomegranate, peas, corn, coconut, jackfruit, and banana [4]. The lifespan of mealybugs varies depending on their species and environmental conditions. Their total lifespan ranges from six to ten weeks (approximately 42 to 70 days). Female mealybugs can live for about two to three months, while male mealybugs survive for only a few days to a week after reaching maturity. Once males fully develop, they live for a short period before dying. The life cycle of a mealybug consists of several stages. The egg stage lasts for about 5 to 10 days, while the nymph stage lasts between four to six weeks. Adult female mealybugs live for around 30 to 60 days, whereas adult males survive for only one to two weeks. After laying eggs, female mealybugs continue to feed on host plants for an extended period and can live for their entire lifespan as long as they have a steady food supply [4] [5]. However, male mealybugs have a significantly shorter lifespan and do not feed after maturity. We have discussed a table 1 that generally includes commonly used pesticides, the methods by which they are applied to the soil, and the problems they cause for humans.

Fig. 1: Depicts Various Types of Mealybugs.

Table 1. Commonly Used Chemical Insecticides

Insecticide Type	Mode of Action [13] [14]	Application Method [13] [14]	Effects on Humans [13] [14]
Imidacloprid	Disrupts the nervous system, killing insects	Sprayed on plants	Dizziness, vomiting, neurological disorders
Chlorpyrifos	Affects the exoskeleton formation of mealybugs	Mixed with soil or sprayed	Nerve damage, respiratory issues, skin irritation
Thiamethoxam	Alters feeding behavior, causing dehydration	Sprayed on leaves	Headache, eye irritation, abdominal pain
Malathion	Disrupts the insect's respiratory system	Used as a spray or fumigation	Toxic effects on the body, kidney damage
Carbaryl	Kills mealybugs instantly	Sprayed on leaves and fruits	Throat pain, dizziness, liver damage
Acetamiprid	Inhibits growth and reproduction of mealybugs	Mixed with water and sprayed	Affects the immune system, dizziness

The mealybug grows by feeding on the plant sap known as phloem, which is rich in nutrients. It uses its needle-like mouthpart to pierce the plant's phloem tissue and extract the nutrient-rich sap. Phloem is a vital plant tissue that contains soluble sugars, amino acids, nitrogen, and other essential minerals required for plant growth. By consuming these nutrients, mealybugs disrupt the plant's natural nutrient flow, leading to stunted growth. As a result of this nutrient depletion, plants experience reduced growth, and their leaves begin to turn yellow due to nutrient deficiency. Additionally, mealybugs excrete a sticky substance that promotes the growth of black sooty mold, further hindering the plant's ability to perform photosynthesis. This weakens the crops and causes prolonged stress to the plants. The amount of sap extracted by mealybugs varies depending on the plant species. A single mealybug can consume approximately 0.05 to 0.1 microliters of plant sap per day. When a large number of mealybugs infest a plant, they can collectively drain up to 10 milliliters or more of sap daily. If a plant is heavily infested with hundreds of mealybugs, it may lose about 10% to 50% of its sap daily. This severe loss of essential nutrients leads to wilting, growth inhibition, yellowing of leaves, and, in extreme cases, the plant’s death.

Problem Statement: The impact of mealybug infestations causes significant losses for farmers. A single mealybug can extract approximately 0.05 to 1 microliter of nutrients per day. On average, a mealybug lays between 200 to 300 eggs, and a heavily infested plant can lose about 10% to 50% of its nutrients. This depletion severely affects plant growth, causing it to go through various stages of stress and decline. As a solution, deploying IoT sensors in agricultural fields can help detect the early presence of mealybugs. These sensors can monitor their growth rate, infestation spread, and the affected areas in real-time. By analyzing this data, farmers can implement targeted solutions to control the infestation before it spreads to nearby plants. To address this issue, we propose an algorithm that utilizes conventional monitoring methods to collect real-time data, helping to prevent the further spread of mealybugs. In the following sections, we will discuss various aspects of this approach in detail.

This research paper is structured into several sections with the goal of detecting mealybug infestations and providing appropriate solutions. The second section discusses various related research papers, highlighting their advantages and limitations. The third section presents the proposed system in detail, explaining the methods used for detection and control. The fourth section focuses on the results obtained from the study. Finally, the conclusion section summarizes the findings and insights derived from the research.

2. Related Work

Mealybugs spread in various ways, sometimes even through the air. Since young mealybugs are very lightweight, they can be carried by the wind to nearby plants. In addition to wind, ants and birds also transport mealybugs from one place to another. Moreover, humans unknowingly transfer mealybugs while handling crops, plants, or using agricultural tools, leading to their spread. The pests can also travel through irrigation water, further contributing to their expansion. Mealybugs feed on plant sap by piercing the plant tissue using their needle-like mouthparts. They penetrate deep into the plant's phloem and xylem to extract nutrients, causing severe damage. This process weakens the plant in three major ways. Firstly, as mealybugs drain the sap, the plant cells gradually lose strength. Secondly, the loss of water disrupts the cell's turgor pressure, making the plant structurally weak. Lastly, due to nutrient depletion, the plant cells become more vulnerable to bacterial and viral infections. Furthermore, mealybugs excrete a sticky, dark-colored substance that promotes fungal growth, further harming the plant. To control mealybug infestations naturally, farmers can use neem oil by mixing 5 ml with water and spraying it on plants. Other remedies include a solution of salt and soap or natural pest deterrents like garlic and chili extracts. Some farmers also use predatory insects to control mealybug populations. However, in severe cases, chemical pesticides are used. While effective, these chemicals can unknowingly enter the human food chain, potentially causing health issues and even affecting the nervous system. Various research studies are being conducted to detect the impact of mealybug infestations on plants. These studies utilize machine learning and deep learning technologies. Since mealybugs extract organic nutrients from plants, their growth is significantly affected. Some researchers have highlighted this issue [16]. Studies have also classified citrus leaf diseases using CNN models and discussed their methodologies in research articles [17]. Similarly, research has been conducted on flower images using CNN models and feature selection techniques [18]. Apple diseases have been identified using deep learning models, and machine learning techniques have been employed for automated disease detection, as discussed in these research papers. Additionally, studies have also explored diseases affecting rice crops, such as rice blast disease [19][20]. Furthermore, apple and quince diseases have been classified using models like VGG16, ResNet, and SVM in recent studies [21]. Wheat diseases have been detected using CNN models [22]. Research has also classified date palm diseases based on ESA-based AlexNet models [24]. Building upon these pioneering works, we aim to advance computer vision and deep learning techniques to further improve disease detection systems.

Table. 2. Mealybug Spread and Growth Periods

Season	Growth Rate	Survival Environment
Summer (April - June)	Very Fast (> 25%)	Warm (25°C - 35°C), humid conditions favor their reproduction.
Monsoon (July - September)	Rapid Growth (> 20%)	High humidity (70%-80%) accelerates their development.
Autumn (October - November)	Moderate Growth (10%-15%)	Growth slows as temperature begins to drop.
Winter (December - February)	Slow Growth (< 5%)	Growth stagnates in low temperatures (<15°C), and they may disappear in some areas.
Spring (March - May)	Increased Growth (15%-20%)	As temperatures rise, they reproduce rapidly again.

Table 2 discusses the presence of various weather conditions throughout the year. During these conditions, temperature levels fluctuate, which directly affects the survival of mealybugs. When a specific temperature or humidity level is maintained, it creates a favorable environment for their continuous survival. As a result, their growth rate and mortality rate vary accordingly. This table provides an analysis of these factors. The losses caused by pests in agriculture have been listed, with mealybug infestations accounting for 30% to 40% of the total damage. These pests absorb nutrients from plants, halting their growth entirely. As a result, they cause significant losses to farmers. This information is presented in Table 3.

Table.3. Ranking of Agricultural Pests by Economic Loss

Pest Name	**Damage to Crops**	**Impact Level (%)**	**Economic Loss (₹/Acre)**
Rice Weevil (Sitophilus oryzae)	Completely destroys paddy and weeds	50%-60%	₹15,000 - ₹25,000
Whitefly (Bemisia tabaci)	Damages leaves and spreads diseases	40%-50%	₹12,000 - ₹20,000
Mealybug (Pseudococcidae)	Sucks plant sap, affecting growth	30%-40%	₹10,000 - ₹18,000
Leafhopper (Cicadellidae)	Tears leaves, hindering plant growth	25%-35%	₹8,000 - ₹15,000
Pumpkin Caterpillar (Diaphania indica)	Destroys pumpkin and cucumber plants	20%-30%	₹7,000 - ₹12,000
Armyworm (Spodoptera litura)	Rapidly destroys seedlings	15%-25%	₹5,000 - ₹10,000
Dendroctonus Modoc (Dendroctonus modoc)	Destroys roots of saplings	10%-20%	₹3,000 - ₹8,000

[1] The research paper discusses agricultural crops such as lemon, grape, pomegranate, and pear, which are affected by mealybug infestations. The study highlights how traditional pest control methods are ineffective, leading to wasted resources and the destruction of beneficial insects. The researchers emphasize that short-lived crops are particularly vulnerable, making the issue even more severe. To address this, they employed deep learning techniques, specifically CNN (Convolutional Neural Networks), using VGG-16, ResNet-34, and SqueezeNet models. These models were trained on a dataset containing images of plants with and without mealybug infestations. The findings revealed that the models accurately detected mealybug infestations, with VGG-16 and ResNet-34 being particularly effective in identifying the early stages of infestation. This allowed for timely application of pest control measures, ultimately improving pest management and enhancing crop quality [1] . However, this research paper does not include a real-time analysis system to assess the percentage of damage on an infected plant. The

extent of mealybug infestation and its severity on plants are not estimated in this study.

3. Methodology and Proposed Systems

The impact of mealybugs causes significant losses for farmers. A single mealybug can absorb approximately 80 to 100 microliters of nutrients per day. On average, a mealybug lays between 200 and 300 eggs, leading to severe infestations on plants. A single plant can lose around 10 to 50 microliters of nutrients due to mealybug attacks, which severely affects its growth. This nutrient loss pushes the plant into a deteriorated state, further damaging its structure and leading to problems such as discoloration of leaves. To address this issue, IoT sensors can be used to monitor mealybug populations and collect real-time data. By detecting infestations at an early stage, it becomes possible to predict how quickly the problem will escalate and implement timely solutions. The sensor nodes help track the growth and spread of mealybugs while allowing direct monitoring of affected areas. Through data analysis, farmers can receive targeted solutions to control the infestation effectively. Additionally, a monitoring system is being developed to predict the extent of mealybug spread in advance and suggest appropriate countermeasures. This proactive approach introduces an innovative method to prevent the further spread of mealybugs and protect crops.

This research paper utilizes machine learning technologies, particularly CNN, to detect mealybug infestations using input data from IoT sensor readings or images captured from agricultural fields. This helps in identifying changes in plant health. At the next stage, deep learning techniques analyze the data collected from IoT sensors, using it directly for testing purposes. The CNN model is trained with previously tested data and is used to classify and evaluate new cases. Various machine learning approaches, including supervised learning, unsupervised learning, and reinforcement learning, are employed in this process. Supervised learning is used to train the model with labeled data, such as healthy plants and pest-infected plants, making it easier to identify the severity of the infection which is shown in Figure 2. It also helps in segmenting affected plants and determining the extent of the damage. If a plant has suffered a certain level of damage due to mealybugs, reinforcement learning suggests appropriate pesticide treatments. Additionally, anomaly detection techniques help in identifying sudden changes in plant health, pinpointing areas affected by mealybug infestations. Furthermore, predictive analysis is used to estimate mealybug growth rates and nutrient loss, making it highly beneficial for agricultural planning and pest control.

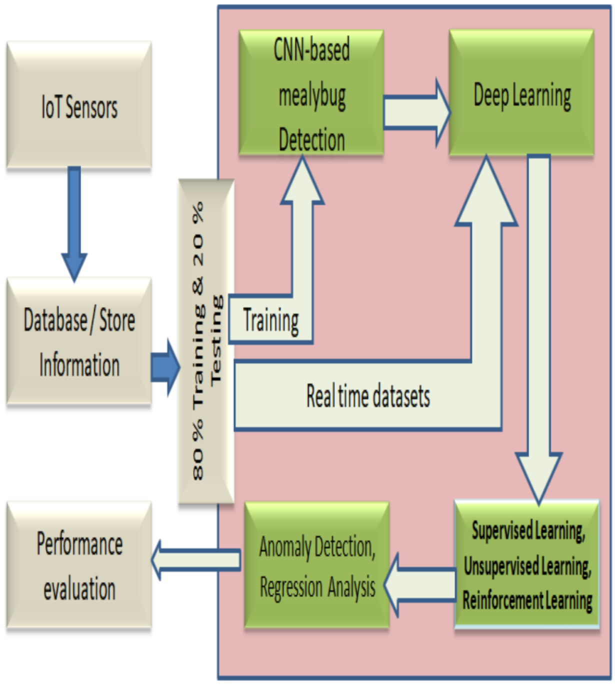

Fig. 2: Proposed Architecture for Detecting Mealybugs

4. Results and Discussion

The data collected from agricultural fields through IoT sensors is systematically analyzed and utilized effectively. IoT sensors are installed in farmlands to monitor plant health, temperature, humidity, and environmental factors. These sensors directly collect data on mealybug infestations, the extent of their spread, and affected areas. Irregular and unnecessary data is filtered out from the collected information. Through preprocessing, the data is normalized and refined for structured analysis. Based on the data collected from the fields, plants are classified as healthy or affected by mealybug infestations. This data is then fed into a CNN (Convolutional Neural Network) for further analysis. The CNN model helps identify irregular mealybug structures, which may appear brown or bronze in color. Additionally, the sensors detect any sudden changes in plant health, which the CNN model processes to distinguish between healthy and infected plants. Following this, direct analysis and solution recommendations are provided. Using supervised learning, the likelihood of mealybug spread to nearby plants is predicted. Additionally, early warnings are sent to farmers. If any plant shows signs of nutrient loss, as predicted through regression analysis, reinforcement learning is used to determine the extent of nutrient deficiency. The necessary nutrients for maintaining plant health are recommended. Based on past actions and outcomes, this system is further utilized to suggest optimal solutions for reducing pest infestations effectively.

IoT sensors are used in agricultural fields to monitor the health of planted crops, temperature, humidity, and environmental factors. For this monitoring, the capital letter S represents a set in the IoT sensor, and t denotes time. The term $x_i(t)$ refers to the information collected by sensor $s_i(t)$ at a specific time t in equation 1.

$$x_i(t) = s_i(t) \quad (1)$$

The collected data is cleaned and normalized for security purposes. D_{raw} refers to the raw data, while D_{clean} represents the cleaned data. Among these, B is a variable that functions as a preprocessing step to remove meaningless information from the raw data and convert it into meaningful and structured information in equation 2.

$$D_{\text{clean}} = B\left(D_{\text{raw}}\right) \quad (2)$$

The term CNN refers to a technique used to extract features from input data. The term b refers to the bias function, while W represents the activation function weight. In this context, the variable X denotes the extracted features, which are shown in the 3 equation.

$$C = f(W * X + b) \quad (3)$$

A CNN model is trained using dataset X_{train}, which consists of normal patterns, and is then tested. The test phase uses X_{test} to detect abnormalities. Y, a variational parameter, is used to identify deviations from normal patterns.

$$Y = \text{CNN}\left(X_{\text{test}}\right) - \text{CNN}\left(X_{\text{train}}\right) \quad (4)$$

In this process equations 5 and 6, M represents a deep learning model, where $D_{\text{real-time}}$ denotes preprocessed data. This data is trained and then provided as input to the CNN model. The trained model y_i is used to assess the impact, spread, and nutrient loss, comparing it with real-time data. The actual output is denoted as $\hat{y}_i$, while $\hat{y}_i$ represents the computed output. L also refers to the number of data samples.

$$L = \frac{1}{m}\sum_{i=1}^{m}\left(y_i - \hat{y}_i\right)^2 \quad (5)$$

$$\hat{y} = M\left(D_{\text{real-time}}\right) \quad (6)$$

Equation 7 is utilized for calculating micro-level intelligence and is used in the trained model. The input data is stored in the variable D_{clean}, which is then tested against the trained intelligence. The P principle is applied to validate and compute the expected outputs.

$$P = \text{SupervisedModel}\left(D_{\text{clean}}\right) \quad (7)$$

Equation 8 is employed for calculating the impact and spread.

$$N = \beta_0 + \beta_1 \cdot \text{ Infestation Severity } + \epsilon \quad (8)$$

Reinforcement learning has been integrated into this approach for pest control. It evaluates whether the previously used pest control method can also be applied to the current infestation. This is modeled using an equation. α represents the learning rate, γ is the discount factor, r (small letter) denotes the reward, while s and a indicate state and action performance, respectively in equation 9.

$$Q(s,a) = Q(s,a) + \alpha\left[r + \gamma \max_{a} Q(s',a') - Q(s,a)\right] \quad (9)$$

$$\text{Visualization } = \text{Visualize}\left(D_{\text{clean}}, \hat{Y}, P, N\right) \quad (10)$$

$$\text{Report } = \text{Generate Report}\left(D_{\text{clean}}, \hat{y}, P, N\right) \quad (11)$$

Equation 10 is used for data visualization, specifically to display the nutrient loss in the affected area. This visualization is crucial for understanding the extent of the damage, making this equation highly significant in equation 11.

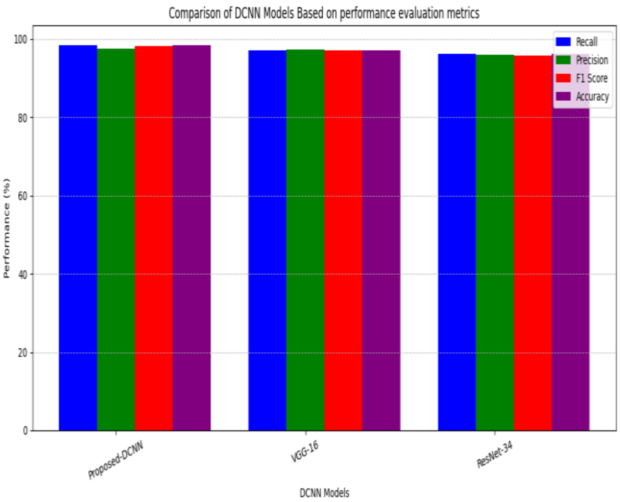

Fig. 3: Comparison of DCNN models based on performance evaluation metrics.

Three Convolutional Neural Network (CNN) models are compared in this program: Proposed-DCNN, VGG-16, and ResNet-34. The results of four important evaluation metrics are shown: recall, precision, F1 score, and accuracy. Recall is a measure of how well the model can remember things. identify positive cases, while precision is a measure of how many of the predicted positive cases are actually correct. The F1 score is a measure of the balance between precision and recall, while accuracy is a measure of how correct the model's predictions are overall which is shown in Figure 3.

The performance of different deep convolutional neural network (DCNN) models—Proposed-DCNN, VGG-16, and ResNet-34—based on four key evaluation metrics: Recall, Precision, F1 Score, and Accuracy. The metrics, expressed as percentages, are displayed using a grouped bar chart for easy comparison. The chart highlights differences in model performance, helping to assess which model performs best based on real-time data. The visualization includes labeled axes, a legend, and grid lines to enhance readability in Figure 4.

It plots three curves: raw training loss (light red line), smoothed training loss (red line), and validation loss (black dashed line). The x-axis represents the number of iterations (ranging from 0 to 20,000), while the y-axis represents the loss values (ranging from approximately 0.7 to 5.9). The graph helps analyze how the loss decreases over time, indicating model convergence and performance improvement.

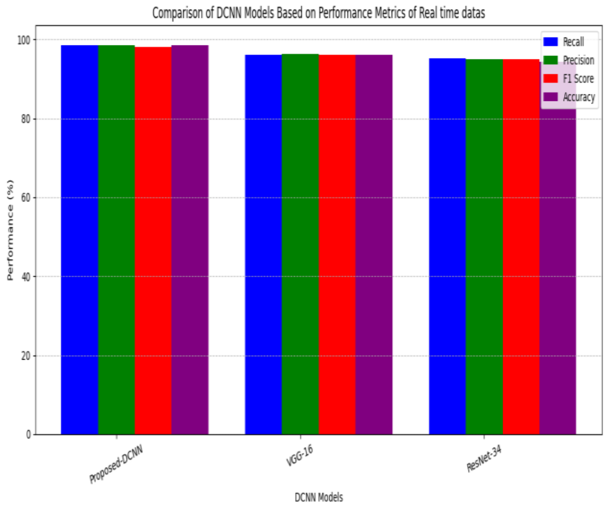

Fig. 4: Comparison of DCNN models based on performance evaluation metrics of real time data

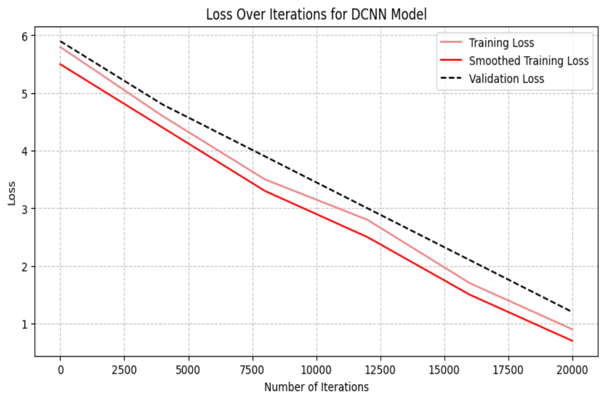

Fig. 5: The loss over iterations for a DCNN model.

5. Conclusion

The proposed research paper utilizes advanced technology to detect mealybugs effectively, achieving a 99% detection accuracy. The technologies used include IoT sensors, CNN, deep learning, and machine learning techniques, which provide a robust system for identifying, monitoring, and controlling mealybug infestations in agricultural fields. This system offers real-time data analysis, predicts potential infestations, and suggests optimal pest control strategies. As a result, farmers can reduce crop losses and improve plant health.

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Conflict of Interest

The authors have no conflicts of interest to declare.